Effective and Equitable Supply of Gasoline to Impacted Areas in the Aftermath of a Natural Disaster

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Abstract

The focus of this research is on supplying gasoline after a natural disaster. There are two aspects for this work: determination of which gas stations should be provided with generators (among those that do not have electric power) and determination of a delivery scheme that accounts for increased demand due to lack of public transportation and considerations such as equity. We develop a mixed integer program for this situation. Two case studies based on Hurricane Sandy in New Jersey are developed and solved in CPLEX. As expected, increasing equity increases cost and also tends to place generators to stations with large initial inventories. It is further observed that CPLEX can solve the largest instances of the problem for a 5 percent tolerance gap, indicating that the model is efficient.

Keywords: humanitarian logistics, disaster operations management, location, allocation

1 Introduction

Many critical activities of today's industrialized societies rely on petroleum-based energy products, especially gasoline. Unfortunately, natural disasters such as hurricanes and earthquakes often cause supply chain disruptions of such petroleum goods due to lack of available supply, lack of ability to deliver the items to the customer, and damage to the transportation infrastructure. Another key aspect is that the requirements for the petroleum goods in question can change significantly as a result of a natural disaster. These supply chain disruptions can severely impede the natural disaster recovery process as seen during the mind-boggling gasoline shortage after 2012's Superstorm Sandy; aggravate an existing food shortage as seen after the 2010 Chilean Earthquake; and raise the prices of petroleum goods as seen after the 2008 China winter storm. These are only a few of the negative impacts that can result from a supply chain disruption of petroleum commodities after a natural disaster. Secondary disruptions are likely due to the shortage of petroleum-based energy products such as oil, diesel fuel, and gasoline. Important examples of such secondary disruptions include the inability of people to go to work and the difficulty with securing basic supplies due to lack of transportation.

Supply chain disruptions of energy commodities, such as gasoline shortages, result in a multitude of problems. For example, after Superstorm Sandy, drivers in the New York City area and parts of New Jersey were waiting for hours in line for the chance to buy gasoline before it ran out. Due to electric power outrage caused by the hurricane, the production of gasoline was disrupted and pumps at some gas stations were inoperable. This gasoline crisis impeded relief and recovery efforts and prolonged the time-period for business operations to return to normalcy. The government took many steps to tone down the problem, such as lifting of restrictions banning certain methods of transporting gasoline by the federal and state government as well as gasoline rationing. Even so, the severe gasoline problem lingered for weeks. Palph Bombardiere, head of the New York State Association of Service Stations and Repair Shops believes "Once the gasoline starts to flow, we'll go back to the same old habits." Gongloff and Chun argued potential solutions to reduce vulnerability to this type of event "could be costly, politically infeasible or both" (Gongloff and Chun, 2012).

In this paper, we focus on planning for effective and equitable distribution of gasoline after a natural disaster. We consider three unique characteristics of the problem: (1) we take account of the increased gasoline demand due to lack of public transportation, (2) we determine which gas stations without electric power should be provided with electric-power generators, and (3) we consider equitable distribution of limited resources. We develop a mixed integer program use Superstorm Sandy as our case study to extensively explore the opportunity of quick recovery.

It is noted that the model and analysis can be applied to other commodities that are typically in short supply after a disaster. For example, it is entirely possible that several grocery stores are out of power after a hurricane event. Restoring power to a grocery store allows the storage of perishable goods such as milk and meat products. There are similarities between the supply chain of perishable goods and that for gasoline which can be exploited to analyze the problem of delivering perishable goods in the aftermath of a natural disaster.

2 Literature Review

We now review the related work that mainly focuses on disaster operations management and emergency logistics. Disaster operations management has four phases: mitigation, preparedness, response, and recovery (Altay and Green, 2006; Caunhye et al., 2012; Galindo and Batta, 2013b).

Several research studies in the disaster management literature concentrate on the disaster response phase. Haghani and Oh (1996) propose a multi-commodity multi-modal network flow model to determine the transportation of emergency supplies and relief personnel. Barbarosoglu and Arda (2004) investigate a two-stage stochastic programming model for the transportation planning of vital first-aid commodities. Özdamar et al. (2004) propose a dynamic time-dependent transportation model, a hybrid model combining the multi-commodity network flow and vehicle routing problems, for emergency logistics planning. Gong and Batta (2007) formulate a model to locate and allocate ambulances after a disaster. Sheu (2007) provides a hybrid fuzzy clustering-optimization approach for efficient emergency logistics distribution. Sheu (2010) proposes a dynamic relief-demand management methodology, which involves data fusion, fuzzy clustering, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), for emergency logistics operations. Caunhye et al. (2015) focus on casualty response planning for catastrophic radiological incidents and propose a location-allocation model to locate alternative care facilities and allocate casualties for triage and treatment.

Some recent research studies consider combining disaster preparedness and disaster response decisions. Mete and Zabinsky (2010) propose a two-stage stochastic programming model for storing and distributing medical supplies and a mixed integer linear program for subsequent vehicle loading and routing for each scenario realization. Rawls and Turnquist (2010) propose a two-stage stochastic mixed integer program for prepositioning and distributing emergency supplies. Lodree et al. (2012) provide a two-stage stochastic programming model for managing disaster relief inventories. Rawls and Turnquist (2012) extend Rawls and Turnquist (2010) to incorporate dynamic delivery planning. Galindo and Batta (2013a) propose an integer programming model for prepositioning emergency supplies for hurricane situations. Rennemo et al. (2014) provide a three-stage stochastic mixed integer programming model for locating distribution centers and distributing aid. Galindo and Batta (2016) incorporate periodic forecast updates for predictable hurricanes and propose a forecast-driven dynamic model for prepositioning relief supplies. Caunhye et al. (2016) propose a stochastic location-routing model for prepositioning and distributing emergency supplies.

In the context of gasoline supply disruption after a natural disaster, the response phase is most relevant. The response actions involve many emergency logistics problems that do not occur in normal daily operations, and include providing food, clothes, and other critical supplies for evacuees and impacted people. These supply problems to help disaster relief operations are often called humanitarian logistics problems Van Wassenhove (2006).

The humanitarian logistics literature that addresses the critical notion of equity is limited (Huang et al., 2012). Fortunately Karsu and Morton (2015) reviewed the equity, balance of optimization models in the operations research. Four types of equity approached was discussed in their paper. Relevant models include a max-min approach for customer satisfaction (Tzeng et al., 2007), a min-max approach for waiting time (Campbell et al., 2008), a multi-objective approach that minimizes unsatisfied demand along with other costs (Lin et al., 2011), and a multi-objective approach that minimizes the maximum pairwise difference in delivery times (Huang et al., 2012). In our paper, we utilize the max-min approach to address equity concerns.

3 Modeling

In the aftermath of a natural disaster, especially when supply chain infrastructures are largely destroyed, supply chain disruption occurs. Gasoline delivery is highly impacted and limited, since there are number of refineries and terminals out of operation. With limited gasoline resource and generators available, effective and equitable gasoline delivery and generator allocation highly impact the recovery and rebuilding of the community. As illustrated in Figure 1, a typical gasoline supply chain consists of four stages: producing/importing crude oil, refining into gasoline, blending gasoline with ethanol, and retailing and transportation between them. A disruption by a natural disaster can happen in any stage (U.S. Energy Information Administration, 2013). Let us take Superstorm Sandy as an example. After Sandy's arrival, a total of 9 refineries in the area were shut down and a total of 57 petroleum terminals were either shut down or were running with reduced capacity (Benfield, 2013). Motivated by such a scenario, we will try to maximize the total gasoline sale of all gasoline stations across the regions, and at the same time incorporate the requirement of equity of delivery across the regions. To capture this objective, we maximize the total gasoline delivery plus equity. Since it is important to fulfill the gasoline demands of the communities to have a speedy recovery from disaster, in our model we will not consider any cost or profit factor, instead we aim at fast and efficient delivery of gasoline. We consider all the related constraints, e.g., gas station capacity. We also consider that each gas station will have a gasoline sale cap, which is usually not the case considered in regular gas station operations. But after Superstorm Sandy, people and cars were waiting in a line to fill gas for their home electric generators and cars. We thus have limited gasoline pumps to fulfill the demands of the community.

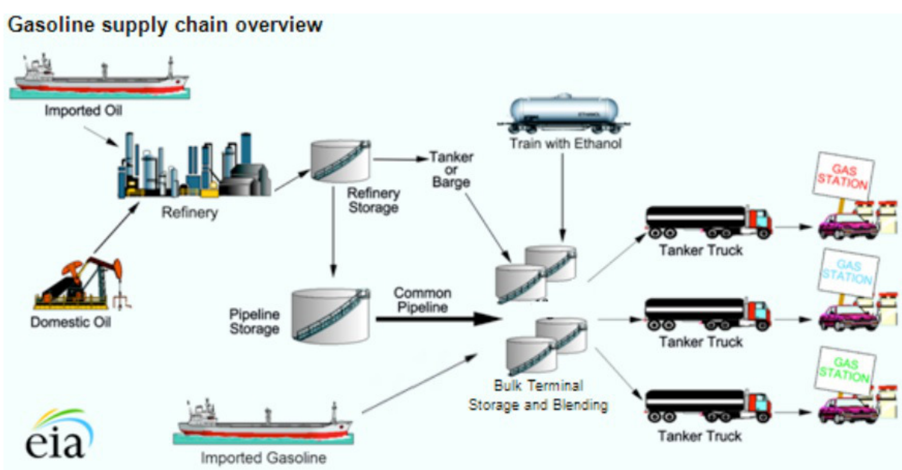

Figure 1: Gasoline Supply Chain Overview (Source: U.S. Energy Information Administration 2013)

Based on the fact that many refineries and petroleum terminals were shut down in the aftermath of Hurricane Sandy, in this paper we assume that we have a single depot for available gasoline resource and delivery trucks. We further assume that this depot will only supply gasoline to the affected regions. There is limited gasoline resource available in this single depot. And because of that, we will also assume each gas station in the affected regions will only demand gasoline. Of course these gas stations will have reserve capacity and sale capacity limitations. After Superstorm Sandy, New Jersey and New York city both ordered a mandatory ration to regulate access to gas stations for a few weeks. So we consider our model with a limited time period. This time period can be as short as a day or as long as a few weeks according to the severity of the aftermath of a natural disaster. We will assume each delivery truck will deliver on a full truck load to one single gasoline station and we cannot partially deliver gasoline. This is typical for gasoline delivery, where a compartment of a truck should ideally emptied to minimize the danger of an explosion due to the creation of gasoline vapour. We can also deliver a few truck loads to a single gas station if one single delivery of gasoline would not satisfy the demand. In the aftermath of Superstorm Sandy, lots of gasoline stations were out of power even though these stations still had gasoline in stock. To address this, we assume a pool of available generators that can be assigned to the gas stations which are out of power. Then, based on the assigned generators, we will assign trucks to deliver full truck load gasoline to those stations.

We assume that there is a set of regions I, indexed by i. Let J be the set of all gas stations in all regions, indexed by j. $J = J_1 \cup J_2$, where J_1 is the set of gas stations with power aftermath and J_2 is the set of gas stations which are out of power. We assume T as the number of time periods. Let G_i be the set of gas stations in region i. For each gasoline station, let W_j be the storage capacity at gas station j, O_j be the maximum output at gas station j, and V_j be the initial storage inventory at gas station j. Now let us assume that there is a set of available generators B. For the simplification of the modeling and at the same time without loss of generality, we assume that there are two types of gasoline delivery trucks available, type 1 truck and type 2 truck. Each truck tank only contains a single compartment (which makes sense after a natural disaster since high demand quantities at gas stations will be highly likely). For the two types of trucks parameters, the total number of available type 1 delivery trucks is denoted by A_1, while the total number of available type 2 delivery trucks is denoted by A_2. Let C_1 be the capacity of a type 1 delivery truck, C_2 be the capacity of a type 2 delivery truck. In our model, we have a combined demand for each region for each time period since we assume that the customers can only fulfill their demands within their residential regions. Let D_{it} represents the total demand in region i at time period t and E_i be the truck delivery efficiency for region i. For example, if region i has a truck delivery efficiency value of 2 in period t, each truck delivering gasoline in region i can be utilized two times in period t. This allows us to make appropriate assignments of trucks to regions during each time period. Finally, we assume that the quantity of available gasoline resource at time t is R_t.

Let s_{jt} denote the variable for usable inventory at gas station j at time t. We want to place generators into gas stations which are out of power aftermath. Let x_j be the binary variable, which is equal to 1 if we locate a generator to gas station j in the set of J_2, 0 otherwise. After placing the generators, we are able to allocate the available gasoline resource to the gas stations. Define y^1_{jt} as the nonnegative integer variable which represents the number of type 1 truck deliveries to the gas station j at time t, and y^2_{jt} as the nonnegative integer variable which represents the number of type 2 truck deliveries to the gas station j at time t. Let q_{jt} be the fulfilled quantity at gas station j at time t. Last, define z as the equity variable with parameter λ. As stated in Section 2, we have selected a max-min approach to modeling equity. This is why we wish to maximize the minimum ratios of total output quantities of the region's demand. Here the ratio of total output quantities of the region's demand signifies a level of service. The constraints in the model are designed to ensure that the equity variable z takes on this value.

The parameter λ comes into play since a multi-objective approach is used, which weights the gas station output with equity. Here λ is the weight of the equity variable, clearly, alternative schemes for handling the multi-objective nature of this problem can be used. For example, a constraint could be set on the value of the equity variable instead of incorporating equity directly in the objective function.

The list of notation is summarized as follows:

Sets

I: The set of regions, indexed by i

J_1: The set of gas stations which still operate aftermath

J_2: The set of gas stations which run out of power aftermath

J: The set of all gas stations, indexed by j. $J = J_1 \cup J_2$

G_i: The set of gas stations in region i

Parameters

T: Time period indexed by t

W_j: The storage capacity at gas station j

O_j: The maximum output at gas station j

V_j: The initial inventory at gas station j

B: Total number of generators available

A_1: Total number of type 1 trucks available

A_2: Total number of type 2 trucks available

C_1: The capacity of type 1 trucks

C_2: The capacity of type 2 trucks

E_i: Efficiency of truck delivery for region i

D_{it}: The total demand of region i at time period t

R_t: The total available gasoline resource at time period t

λ: The parameter for equity variable

Decision Variables

s_{jt}: The usable inventory variable for gas station j at time period t

x_j: Binary variable equal to 1 if a generator is located at gas station j, 0 otherwise

y^1_{jt}: The integer variables for the number of type 1 truck deliveries to gas station j at time t

y^2_{jt}: The integer variables for the number of type 2 truck deliveries to gas station j at time t

q_{jt}: The output of gas station j at time period t

z: The equity variable

The following linear integer program model represents our formulation:

$$\text{[Obj]} \quad \max \sum_{t=1}^{T} \sum_{j \in J} q_{jt} + \lambda z \tag{1}$$

$$\text{s.t.} \sum_{j \in J_2} x_j \leq B, \tag{2}$$

$$s_{j,0} = V_j, \qquad \forall j \in J_1, \tag{3}$$

$$s_{j,0} = x_j V_j, \qquad \forall j \in J_2, \tag{4}$$

$$s_{j,t} = s_{j,t-1} + C_1 y^1_{j,t} + C_2 y^2_{j,t} - q_{j,t}, \qquad \forall j \in J, \text{ for } t = 1, 2, ..., T, \tag{5}$$

$$q_{jt} \leq O_j, \qquad \forall j \in J, \text{ for } t = 1, 2, ..., T, \tag{6}$$

$$C_1 y^1_{jt} \leq W_j x_j, \qquad \forall j \in J_2, \text{ for } t = 1, 2, ..., T, \tag{7}$$

$$C_2 y^2_{jt} \leq W_j x_j, \qquad \forall j \in J_2, \text{ for } t = 1, 2, ..., T, \tag{8}$$

$$s_{j,t-1} + C_1 y^1_{jt} + C_2 y^2_{jt} \leq W_j, \qquad \forall j \in J, \text{ for } t = 1, 2, ..., T, \tag{9}$$

$$q_{jt} \leq s_{j,t-1} + C_1 y^1_{j,t} + C_2 y^2_{j,t}, \qquad \forall j \in J, \text{ for } t = 1, 2, ..., T, \tag{10}$$

$$\sum_{j \in G_i} q_{jt} \leq D_{it}, \qquad \forall i \in I, \text{ for } t = 1, 2, ..., T, \tag{11}$$

$$\sum_{i \in I} \sum_{j \in G_i} (1/E_i) y^1_{jt} \leq A_1, \qquad \text{for } t = 1, 2, ..., T, \tag{12}$$

$$\sum_{i \in I} \sum_{j \in G_i} (1/E_i) y^2_{jt} \leq A_2, \qquad \text{for } t = 1, 2, ..., T, \tag{13}$$

$$\sum_{j \in J} (C_1 y^1_{jt} + C_2 y^2_{jt}) \leq R_t, \qquad \text{for } t = 1, 2, ..., T, \tag{14}$$

$$z \leq \frac{\sum_{j \in G_i} q_{jt}}{D_{it}}, \qquad \forall i \in I, \text{ for } t = 1, 2, ..., T, \tag{15}$$

$$x_j \in \{0, 1\}, \qquad \forall j \in J, \tag{16}$$

$$s_{jt} \geq 0, \qquad \forall j \in J, \text{ for } t = 1, 2, ..., T, \tag{17}$$

$$q_{jt} \geq 0, \qquad \forall j \in J, \text{ for } t = 1, 2, ..., T, \tag{18}$$

$$y^1_{jt}, y^2_{jt} \in I^+, \qquad \forall j \in J, \text{ for } t = 1, 2, ..., T, \tag{19}$$

$$z \geq 0. \tag{20}$$

The objective function (1) is to maximize the total fulfilled gasoline outputs plus equity. Constraint (2) makes sure that the number of generators that we will locate in the set J_2 is less than or equal to the total number of available generators. Constraint (3) assigns initial inventory for the set J_1. Constraint (4) assigns initial inventory for the set of J_2 since only inventories in those gas stations located with generators are countable. Constraint (5) sets next period usable inventory for each gas station at time period t. Constraint (6) ensures that the fulfilled gasoline quantity at each gas station is less or equal to the maximum output of the gas station at time period t. Constraints (7, 8) ensure that only gas stations located with generators in the set J_2 can have gasoline deliveries. Constraint (9) makes sure that the usable inventory is less than the capacity of the gas station. Constraint (10) ensures the fulfilled gasoline output is less than or equal to the usable inventory of the gas station at time period t. Constraint (11) makes sure that the total output quantity in each region is less than or equal to the regional demand at time t. Constraints (12, 13) ensure that the number of utilized trucks does not exceed the total number of available trucks of each type. Constraint (14) makes sure the total allocated gasoline resource could not exceed the available resource at time t. Constraint (15) is the equity constraint. Here we set our equity as the maximum of the minimum ratio of total output quantities over the region's demand. Constraint (16) is the binary constraint to place generators. Constraints (17), (18), and (20) are the nonnegative constraints since we cannot sell any gasoline if our inventory stock is negative. Constraint (19) is the nonnegative integer constraint which means that we could deliver multiple truck loads of gasoline to one single gas station based upon appropriate situations, e.g., the gas station is the only station that is still open within the region. In the sections that follow, intuitions and deductions are italicized to enhance readability for a practitioner/decision maker.

4 Numerical Example

We now provide a numerical example to explain the model. For simplicity, we will only consider four small regions with gas stations. Figure 2 shows the regions, along with a gasoline station diagram where gas stations with/without power are indicated. In order to simplify the display, we will just assume that the single depot is located in the center of four regions. We test different efficiency parameters for different regions. If the efficiency parameter is 2, it means that each single truck can transport two truck loads to the region. Thus the utilization of each type of truck assigned to those regions with efficiency parameter 2 will be doubled. Table 1 lists all the parameters and their values.

We tested three values of λ: 0, 100, and 200 for different equitability scenarios to gain a perspective on the impact of parameter λ on the performance. We run this model using IBM ILOG CPLEX for a total of three scenarios. All these scenarios utilize the same parameter data set as listed in Table 1. For scenario 1, we set parameter λ for equitability z as 0, scenario 2 with the value of λ as 100, and scenario 3 with the value of λ as 200. Figures 3 and 4 shows the results of where we are going to place the generators for different scenarios.

From Figure 3, we can see that, for scenario 1 where the value of λ is zero, we tend to place the only 2 available generators to gas stations 4 and 6 with the objective value of 212. *When the equity parameter λ is zero, our goal is to maximize the total gasoline sale. Hence placing the two available*

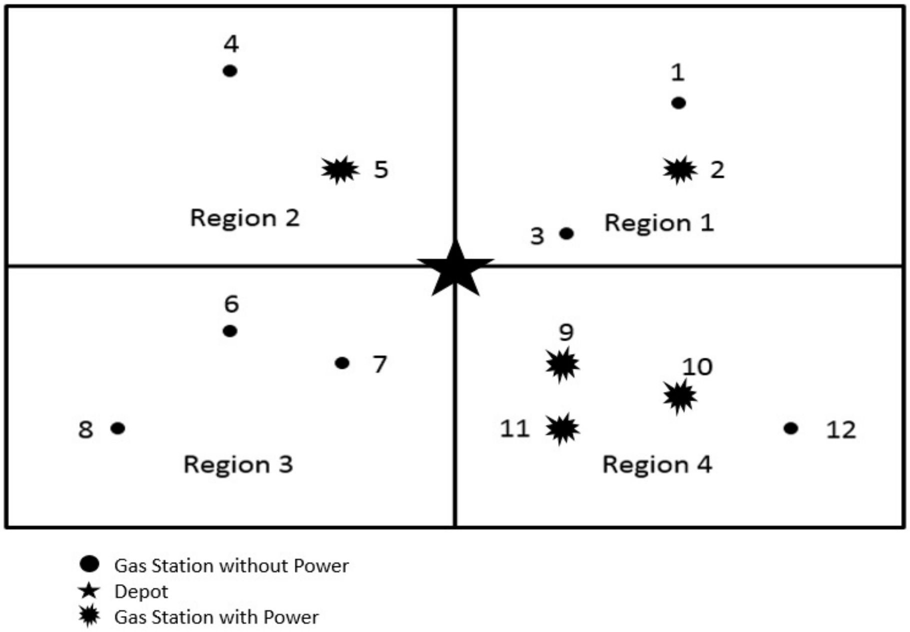

Figure 2: An Illustrative Example.

Table 1: Parameter Values

Parameter	Description	Value
I	Set of regions	$\{1, 2, 3, 4\}$
J_1	Set of gasoline stations which still operate aftermath	$\{2, 5, 9, 10, 11\}$
J_2	Set of gasoline stations which run out of power aftermath	$\{1, 3, 4, 6, 7, 8, 12\}$
J	The set of all gas stations, indexed by j. $J = J_1 \cup J_2$	$\{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12\}$
W_j	The storage capacity at gas station j	20, 10, 8, 24, 30, 26, 12, 18, 20, 24, 30, 26
O_j	The maximum output at gas station j	10, 5, 4, 12, 15, 14, 6, 9, 10, 12, 15, 13
V_j	The initial inventory at gas station j	12, 2, 3, 20, 4, 19, 6, 12, 0, 12, 5, 18
T	Time period indexed by t	1, 2, 3, 4, 5
B	Total number of generators available	2
A_1	Total number of type 1 trucks available	3
A_2	Total number of type 2 trucks available	6
C_1	The capacity of type 1 trucks	10
C_2	The capacity of type 2 trucks	6
D_{it}	The total demand of region i at time period t	100 for each region at period t
R_t	The total available gasoline resource at time period t	30 for each period t
E_i	Efficiency of truck delivery for region i	E_1=3, E_2=2, E_3=2, E_4=3
λ	The parameter for equity variable	0, 100, 200

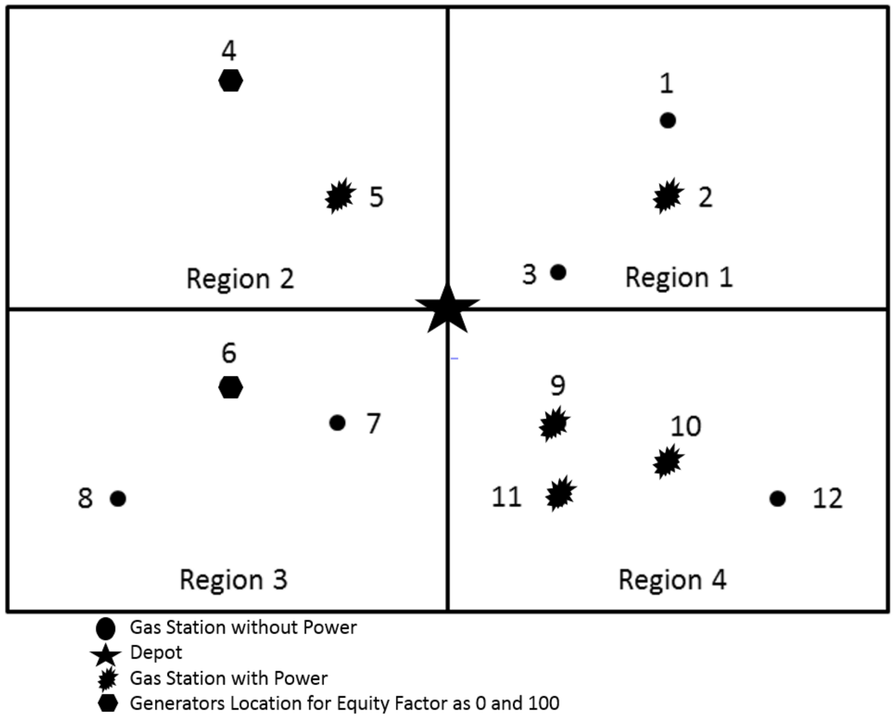

Figure 3: Generator Placement for the Illustrative Example.

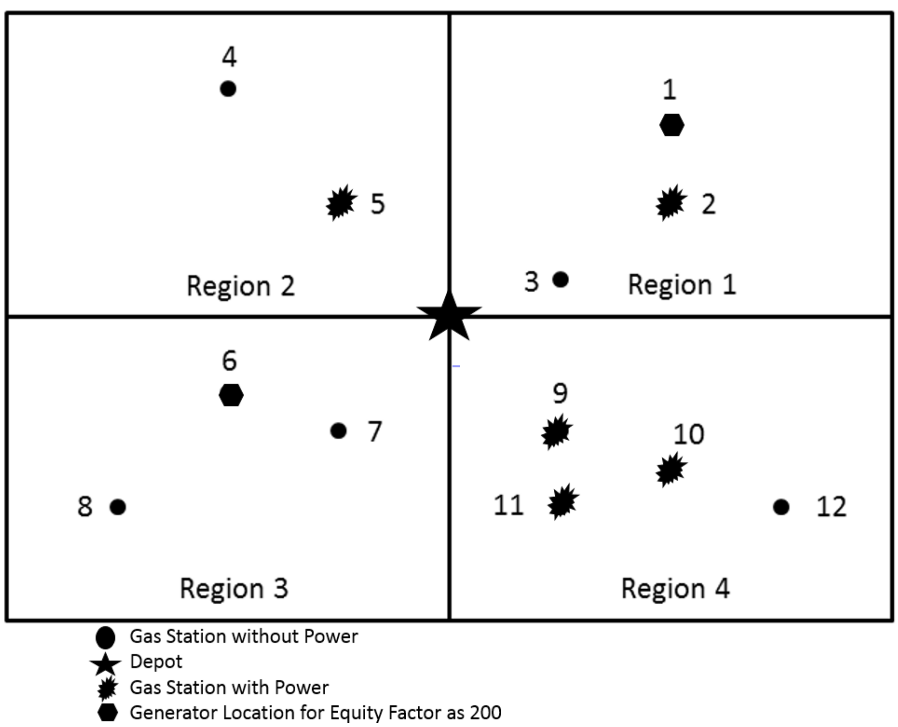

Figure 4: Generator Placement for the Illustrative Example (continued).

generators at gas stations 4 and 6 is optimal since these two gas stations have the largest initial gasoline inventory. Consider scenario 2 in Figure 3, in this case, we will still place the two available generators to gas station 4 and gas station 6, but since we slightly increase the weight of the equity factor λ to 100, we obtain the objective value of 216.67 with the equity value z=0.0467. *When we increase the weight of the equity parameter λ (but not large enough to overcome the impact of large initial inventories), we still place our available generators at gas stations with large initial inventory.* Now let us look at scenario 3 in Figure 4 where the value of λ is equal to 200. In this case, we place the two generators at gas station 1 and gas station 6 which will produce the objective value of 224 while generating the largest equity value z as 0.1 across these three scenarios. We note that the first two scenarios only produce equity values 0 and 0.0467, respectively.

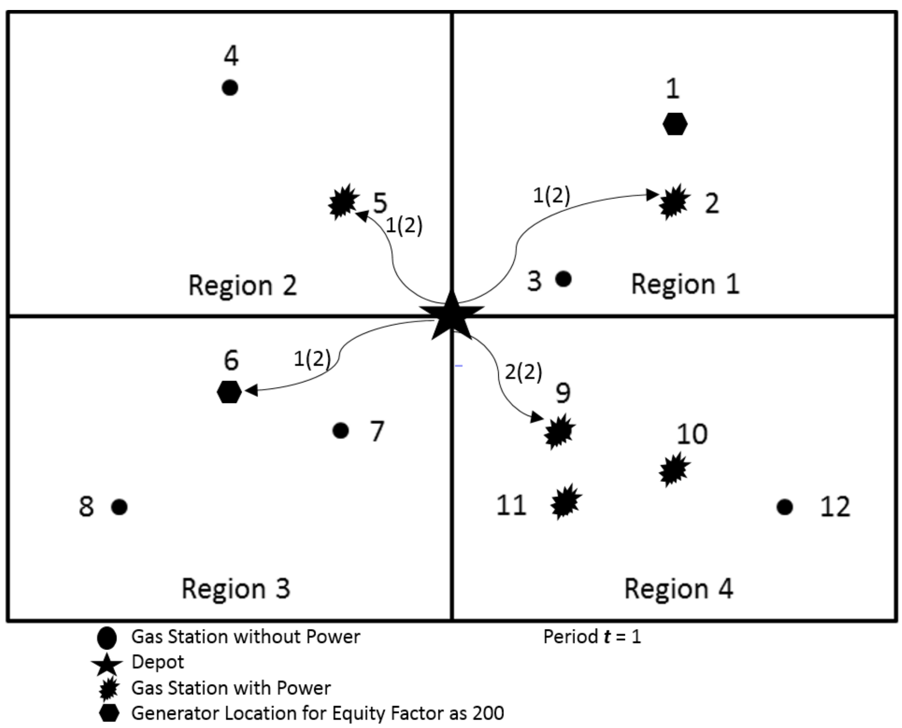

Figure 5: Truck Assignments for Scenario 3 Period 1.

In our numerical study we test 5 periods. Figures 5–9 provide us detailed information regarding truck assignments for each period. In these five figures, the numbers above the arrows means numbers of each type of delivery trucks. For example, in Figure 5, 1(2)above the arrow means one type 2 truck, 2(2) means two type 2 trucks, 1(1) in Figure 6 means one type 1 truck etc. The case that we show in Figures 5–9 is for scenario 3 where the value of the equity factor λ is 200. From

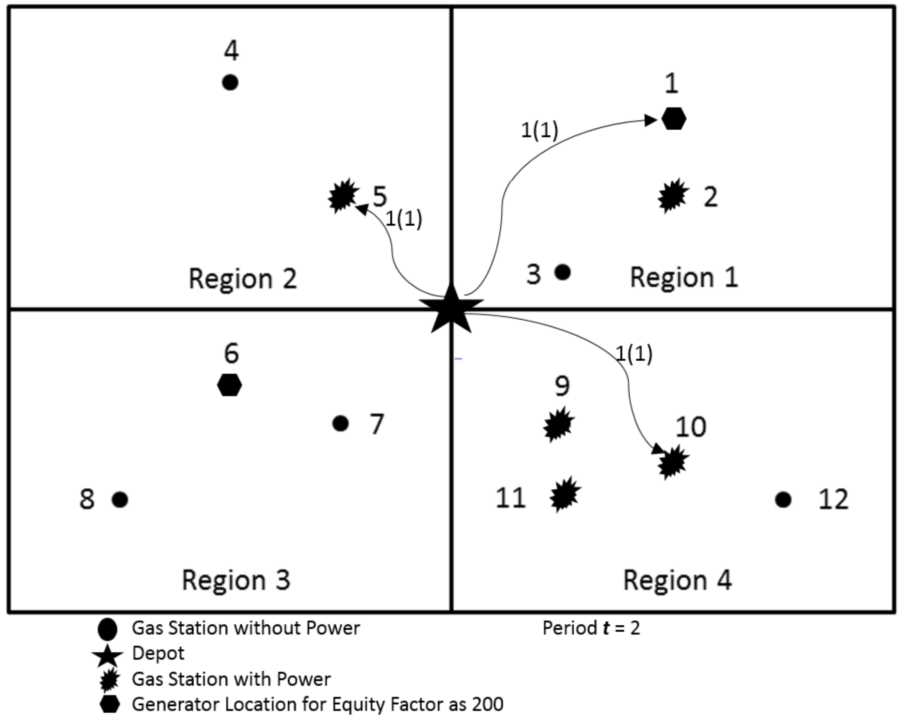

Figure 6: Truck Assignments for Scenario 3 Period 2.

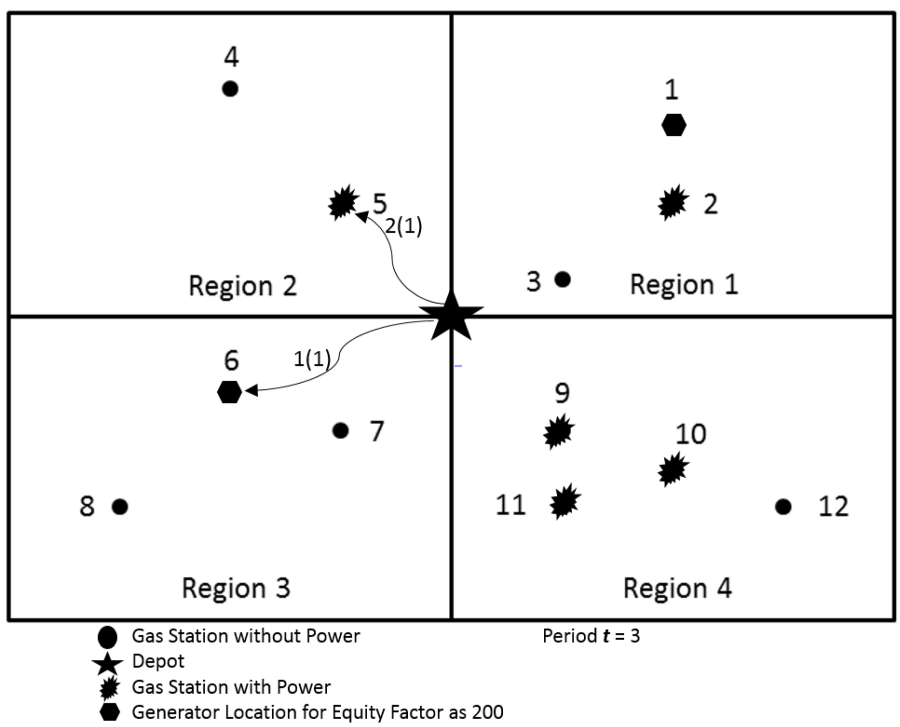

Figure 7: Truck Assignments for Scenario 3 Period 3.

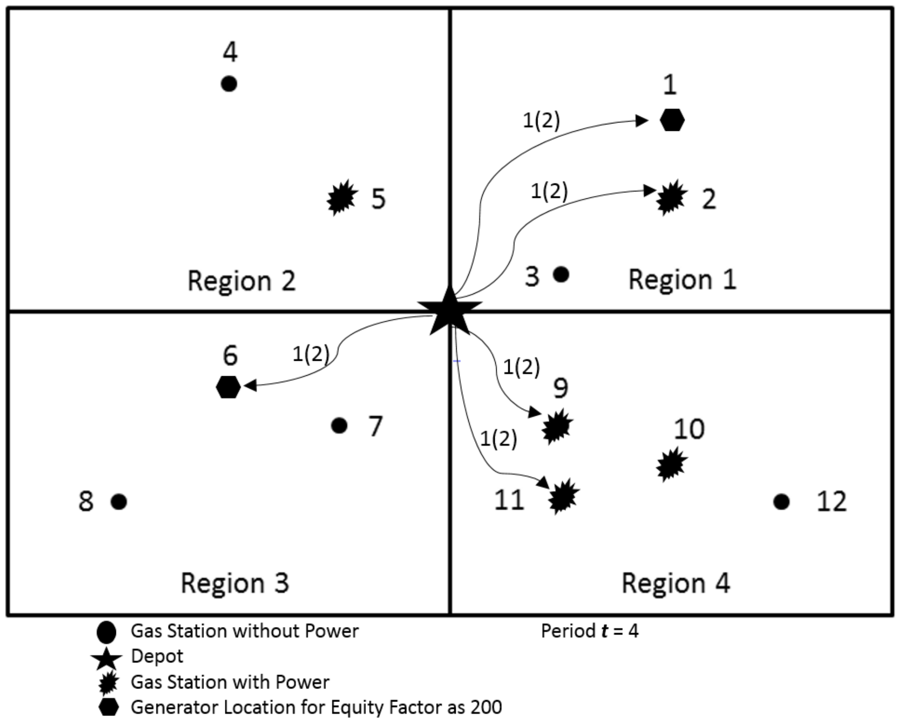

Figure 8: Truck Assignments for Scenario 3 Period 4.

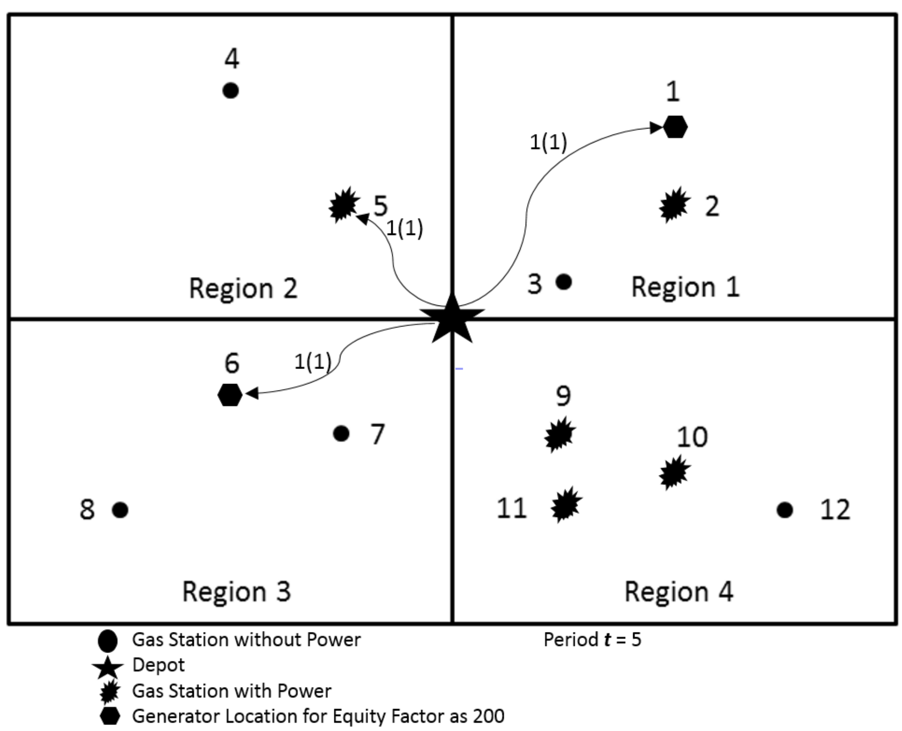

Figure 9: Truck Assignments for Scenario 3 Period 5.

Figure 5, we can see that for period 1, we will assign one type 2 truck to gas stations 2, 5, and 6 and two type 2 trucks to gas station 9 since gas station 9 has power but with zero initial inventory available. As for period 2 in Figure 6, we will assign one type 1 truck to gas stations 1, 5, and 10. In period 3 from Figure 7, we will continue to assign two type 1 trucks to gas station 5 and one type 1 truck to gas station 6. We then assign one type 2 truck to gas stations 1 ,2, 6, 9, and 11 in period 4 as in Figure 8. Finally, in period 5 showed in Figure 9, one type 1 truck is assigned to gas stations 1, 5, and 6. The total sale value is 204 for all periods with 42, 40, 40, 41 and 41 for each period, respectively. As we mentioned earlier, for scenario 3 we have the value of the equity factor λ as 200 and an equity variable value of 0.1. Our finally objective is 224, including the total sale quantity and equity weight. From this numerical case study we can see that our model is quite flexible and sensitive when we want to maximize sale quantity with the equity weight considered. *We can see that as the value of λ increases, the equity variable z and the objective value gets larger. To maximize the outputs of all gasoline stations, we tend to place generators at stations with large initial inventories. However when we increase the value of equity parameter λ, we tend to evenly distribute generators so as to improve the equity value.*

5 Case Study for Two Counties in the State of New Jersey

In late October of 2012, Superstorm Sandy hit the Eastern Coastal areas of the United States. The total loss or damage by Superstorm Sandy was roughly 72 billion dollars. Among them, the State of New Jersey and New York City were badly hit by Sandy (Benfield, 2013). In this case study, we utilize gasoline station data we obtain from the New Jersey Office of GIS Open Data source online to apply our model (New Jersey Office of GIS, 2016). After Superstorm Sandy, most of the refineries and terminals were shut down due to the damage of the storm, the State of New Jersey encountered gasoline shortage and trucks are waiting in the line to fill gas. Houses, cars, and trucks etc were out of power, and the need of gasoline dramatically increased, trucks and individuals were lined up in the queue to wait for gas fulfillment.

Among counties in the State of New Jersey, we pick Monmouth and Ocean Counties for our case study since these two counties are the most hit counties across New Jersey state. Figure 10 provides a glance at the gas station map in these two counties. After Superstorm Sandy, about 40 percent of gasoline stations in New Jersey were closed either because of power loss or gasoline

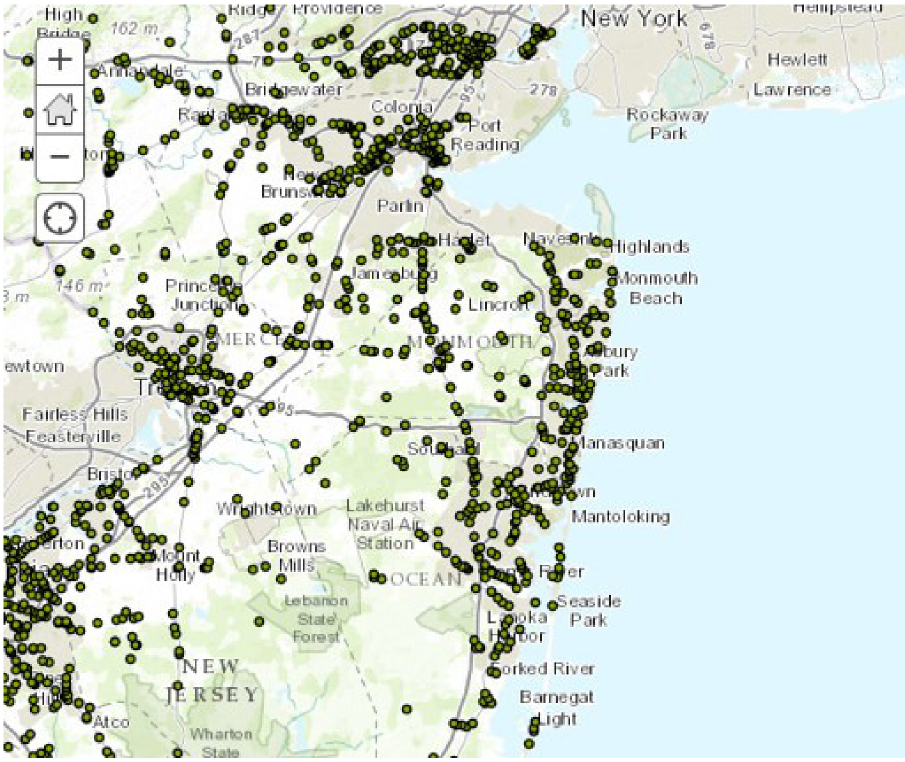

Figure 10: Gas Station Map for Monmouth and Ocean Counties in New Jersey

shortage (Smith, 2012). In this case study, we will consider the case with 40 percent of gas stations out of power. In order to reflect the fact of the gasoline demand crisis, we will assume our demand is three times of maximum gasoline outputs for all gasoline stations within the region. The gasoline stations within the same region will share the demand of the region. We also assume customers within the region will be only served by the gasoline stations in the region.

Since we only have the gas station location information, it is impossible to get all the parameters for each single gas station. So we randomly generate parameters such as W_j the storage capacity at gas station j, O_j the maximum output at gas station j, and V_j the initial inventory at gas station j. We randomly generate the storage capacity of gas stations within a range of 8000 gallons to 35000 gallons, and generate initial inventory V_j of each gas station j randomly within a range of 0 gallon to W_j (the storage capacity at gas station j). Then we assume the maximum output of each gas station j is half of its respective storage capacity. Based on the same set of gas station parameter data, we construct 12 cases in two groups. For each of the 12 cases, we generate 30 replications based on the fact that 40 percent of gasoline stations are out of power. So for each replication, we randomly select gas stations and let these stations have power. These 30 replications are shared by each individual case so that we can conduct valid comparisons on the same data set. All 12 cases are developed based on the factors of truck numbers, truck capacities, number of available generators, equity parameter λ, available resource and region efficiencies. We run our cases by IBM ILOG CPLEX (version 12.6.1) with a computer processor of Intel (R) Xeon (R) CPU e5-2630 v3 @2.4GHz and 32GM installed memory (RAM). In order to speed up the case study all cases are run with a 5 percentage of tolerance gap from optimal.

As we said previously, we conduct these 12 cases in two different groups. One group consists of 8 cases. All these 8 cases are generated by differentiating truck parameters while keeping the same total delivery capacity. Table 2 provides detailed information regarding each individual case. For each case, there are 72 regions, 453 gas stations, 12 periods, 30 generators, an equity parameter weight $\lambda = 2 \times 10^9$, resource at period t $R_t = 10^6$, and region efficiency = 2. The objective value, equity z, total delivery, and CPU time are average values of the 30 replications for each single case. From Table 2 (rows with parameter changes are boldfaced), we can see that, with the same total delivery capacity 1,150,000 gallons in total, the size and numbers of each type of truck affect our result quite significantly. We see that when we have more trucks with smaller capacities for both types of trucks, e.g., cases 3, 4, 6, and 7, our objective value, total delivery quantities and equity variable can all achieve better results while the CPU solving time tends to take much longer. While in the cases where we have large capacities of trucks, e.g., cases 1, 5, and 8, our solution solving time improves dramatically without sacrificing the objective value and equity much. As for case 2, we see that if we have really unbalanced number of types of vehicles and the truck capacity is relatively large, the total delivery quantity is not affected much. We actually improve the solution solving time but with the sacrifice on equity and objective value.

For group 2, we pick one of the cases in the previous group (case 8). Then we fix the trucks parameters, such as number of available trucks and capacity of each different size of trucks. We simply change one parameter for each case as listed in Table 3. Similar to group 1, We run each of 30 replications again for these 5 cases. The results are listed in Table 3. Here, each case have 72 regions, 453 gas stations, 12 periods, 34 type 1 trucks, 15,000 type 1 truck capacity, 80 type 2 trucks, and 8,000 type 2 truck capacity. Again, the objective value, equity z, total delivery, and CPU time are averaged cross 30 replications for each case. Case 8 serves as the baseline for this group. *We see*

Table 2: 8 Cases with the Same Delivery Capacity

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Number of type 1 trucks	50	2	36	59	71	59	71	34
Capacity of type 1 trucks	15,000	14,000	13,000	12,000	11,000	10,000	9,000	15,000
Number of type 2 trucks	50	132	124	68	41	80	88	80
Capacity of type 2 trucks	8,000	8,500	5,500	6,500	9,000	7,000	5,500	8,000
Objective value	26,911,776	15,356,380	29,859,632	29,779,899	15,317,239	29,798,549	29,824,764	26,835,218
Equity z	0.0628939	0.0051518	0.0779815	0.0775056	0.0051978	0.0776099	0.0777934	0.0623860
Total Delivery (gallons)	14,332,996	14,326,020	14,263,329	14,278,779	14,277,688	14,276,568	14,266,089	14,358,023
CPU time (s)	11.72	2.12	360.11	397.88	5.79	303.27	234.72	9.91

that if we decrease the equity parameter λ, we will still achieve a similar total delivery quantity. The equity value z is hardly affected although the solution solving time significantly improves. As for case 10, we decrease the number of available generators. Usually generators are very expensive and the stakeholder of the relative parties (e.g. New Jersey government) would not have lots of generators on hand. *Thus the result of case 10 demonstrates that the equity value will drop significantly even though we only reduce 20 generators.* The total delivery drops not much due to the fact that we have very limited resource, while solving time increases quite a bit. Case 11 is quite obvious since we double our available resource. In this case, the objective value, equity value, and total delivery quantity increase significantly while solution solving time just increases a little bit. In case 12, we simply change all the region efficiency values from 2 to 1. It means that, each type of truck can only be utilized once for each single period. But in other cases, each type of truck can by utilized twice in each period. This implies that we have affectively reduced the total number of available trucks. *We see that the solution time is reduced but other values, e.g., objective value, equity, and total delivery actually do not change much. This is because the number of available trucks are enough to carry out the delivery job.*

Table 3: Five Cases with Fixed Truck Parameters

	Case 8	Case 9	Case 10	Case 11	Case 12
Number of generators	30	30	10	30	30
Weight of equity (λ)	200,000,000	200	200,000,000	200,000,000	200,000,000
Resource at t (R_t)	1,000,000	1,000,000	1,000,000	2,000,000	1,000,000
Region efficiency	2	2	2	2	1
Objective value	26,835,218	14,256,237	14,834,092	38,364,007	26,851,117
Equity z	0.0623860	0.0000000	0.0039128	0.0649604	0.0625146
Total delivery (gallons)	14,358,023	14,256,237	14,051,529	25,371,920	14,348,197
CPU time (s)	9.91	0.83	65.93	12.15	6.29

6 Case Study for All Counties in the State of New Jersey

We follow the same process as the previous case study to utilize gasoline station data which we obtain from the New Jersey Office of GIS Open Data source online (New Jersey Office of GIS, 2016). We still consider the case with 40 percent of gas stations out of power. Same as the previous case study, we will assume our demand is three times of the maximum gasoline outputs for all gasoline stations within each region. The gasoline stations within the same region will share the demand of the region. Customers within the region will be only served by the gasoline stations in the region.

We also randomly generate gas station parameters such as W_j, O_j, and V_j. The storage capacity of gas stations will also be generated within the range of 8,000 gallons to 35,000 gallons, and initial inventory V_j of each gas station j randomly within the range of 0 gallon to W_j. The maximum output of each gas station j is half of its respective storage capacity. Based on the same set of gas station parameter data, we construct 8 cases. For all these cases, we will only generate one replication based on the fact that 40 percent of gasoline stations are out of power. All these cases will share the same data set. Again we run these 9 cases by IBM ILOG CPLEX (version 12.6.1) on the same pc as the previous case study. All cases are run with a 5 percentage of tolerance gap from optimal since the data set is really large (e.g., there are a total of 3,387 gas stations in the state of New Jersey). Table 4 provides us detailed information regarding each individual case, with each case having 489 regions, 3387 gas stations, 12 periods, 400 type 1 trucks, 15,000 capacity for type 1 trucks, 500 type 2 trucks, and 8,000 capacity for type 2 trucks. Since the data set is large when we consider all gas stations in New Jersey, the region efficiency parameters are set to 2 for some regions close to the depot and 1 for the rest of regions. *Cases 1, 2, and 3 in Table 4 show us that once we increase the number of available generators, we can obtain a much better equity value while decreasing the solution solving time significantly.* Now let us compare cases 4, 5, and 2 since in these cases we simply change the equity weight parameter value from 0 as in case 4, 20,000 as in case 5, and 200,000,000 in case 2. We see that for the large data set, in order to achieve a better equity value, we have to use a very large value for equity weight parameter. Now compare case 6 with case 2. We see that if we change all the region efficiency parameter to 1, in this case, the change does not affect the results much. The reason is because we have enough trucks available. Last let us compare cases 2, 7, and 8. We see that the available resource affects our objective value very much. When we get more available gasoline resource, our objective value and total delivery increase. The solution solving time for a smaller resource value as in case 8 is significantly longer when we try to achieve a better equity value and total delivery. *From this large case study, we conclude that our model is effective and efficient.*

7 Hazardous Nature of Gasoline Delivery and Future Work

Gasoline and other petroleum-based energy products such as diesel fuel, kerosene, and liquefied petroleum gas (LPG) are considered as 'hazardous materials' (hazmat) as defined by Pipeline and

Table 4: Nine Cases for All Gas Stations in New Jersey

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Number of generators	50	150	300	150	150	150	150	150
Weight of equity (λ)	200,000,000	200,000,000	200,000,000	0	20,000	200,000,000	200,000,000	200,000,000
Resource at t (R_t)	9,000,000	9,000,000	9,000,000	9,000,000	9,000,000	9,000,000	12,000,000	5,000,000
Region efficiency	2, 1	2, 1	2, 1	2, 1	2, 1	1	2, 1	2, 1
Objective value	114,932,000	124,232,295	127,852,956	117,742,400	117,704,400	126,248,192	154,249,049	80,356,812
Equity z	0.0000	0.0450	0.0403	0.0000	0.0000	0.0508	0.0439	0.0408
Total delivery (gallons)	114,932,000	115,162,000	119,797,400	117,742,400	117,704,400	116,078,700	145,469,900	72,205,900
CPU time (s)	3871.96	395.68	338.23	318.48	318.60	319.21	715.62	8,124.81

Hazardous Materials Safety Administration (2013). In hazmat transportation, risk management against accidents with hazmat spills is a critical issue to protect the environment, communities, and the road infrastructure. In the literature of hazmat transportation using trucks, the key attributes in risk management are accident probabilities and accident consequences (Batta and Kwon, 2013; Erkut et al., 2007; Sun et al., 2015; Toumazis and Kwon, 2015; Esfandeh et al., 2016). After a natural disaster, with damaged infrastructure, the probability of hazmat spill increases significantly; hence hazmat transportation can potentially lead to a catastrophic environmental disaster.

In fact, fuel oil, diesel fuel, and gasoline are the three hazardous materials with the highest probability of being involved in a transportation-related accident after a natural disaster. For example, out of 170 cases of accidents involving hazardous materials triggered by flooding reported by the European Directive on dangerous substances, 142 of them were fuel oil, diesel fuel, or gasoline (Cozzani et al., 2010). Thus transport risk should be incorporated as part of model to make it more realistic.

Our model presented in this paper may be extended to consider such hazardous nature of gasoline delivery after a natural disaster as follows to minimize the risk of hazmat accidents during the delivery. First, the model needs to take account of the routing component. The model in this paper only considers delivery schedules, without determining which routes to take to travel between gas stations and the depot. Since the accident probability and consequence are dependent on the routes chosen, the road condition, and the weather condition, a robust routing method based on robust optimization (Kwon et al., 2013) or averse risk measure (Toumazis and Kwon, 2015) will be necessary. Second, a real-time component for monitoring road condition needs to be incorporated. The damages to the road conditions after a natural disaster are often collected with delays, and the situation can be worsened with time, for which case a time-dependent routing method (Toumazis and Kwon, 2013) would be useful. Third, equity of hazmat risk should be considered. In the distribution of gasoline, people near the destination of shipping benefits. On the other hand, people near the shipping routes will be exposed to risk of hazmat spills. Thus, it is important to balance the equity of gasoline distribution (this paper) and the equity of hazmat risk avoidance (Kang et al., 2014).

8 Conclusions

In the aftermath of a natural disaster, the gasoline supply chain may be disrupted. Gasoline shortage may become a key factor to the recovery of the community. In our model, we consider a single depot and two types of delivery trucks with limited gasoline resource in a limited time period. We utilize the limited back up generators and optimize the generators assignment and truck deliveries to the gas stations to achieve maximum gasoline delivery, and at the same time incorporate the equity factor across the different regions.

Our major conclusions are as follows:

- As the equity parameter increases, we get an increase in cost. Thus a tradeoff is needed.
- To maximize output of gasoline stations, we tend to place generators at stations with large initial inventories.
- Increasing the equity parameter tends to evenly distribute generators across stations.
- Reusing trucks when possible does not have a significant effect due to limited supply of gasoline.
- It is important to have a large number of available generators to achieve more equitable solutions.
- The model is effective and efficient, with solution within 5 percent tolerance level achievable for a realistic case study using a commercial solver like CPLEX.

In addition to the future research directions mentioned in Section 7, we also need to understand how individuals seek gas in a gas shortage situation, to evaluate the true impact of our model. Analytical models based on queueing and simulation models and their interactions with the base model presented in this paper would be useful contributions.

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